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Informational Effects of Nutrient Intake Determinants on Cholesterol Consumption

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Nutrition information and dietary data for a sample of U.S. household meal planners are used to estimate the direct and indirect effects of various dietary determinants on cholesterol intake. Holding sociodemographic and household characteristics constant, greater nutrition information translates to significantly lower intake of dietary cholesterol. Evidence supports the hypothesis that schooling promotes better health behavior through greater acquisition and use of health information. Blacks and Hispanics stand to benefit from nutrition education programs to increase their awareness of diet-health relationships. A low-calorie diet decreases the intake of cholesterol more than a low-fat diet.

Key words: cholesterol, health inputs, health production, nutrient demand, nutrition knowledge

Introduction

The growing evidence linking diet and health and the enormous cost of diet-related illness have inspired numerous public-health campaigns to improve the American diet (Frazao; U.S. Department of Health and Human Resources; Willett). The U.S. Department of Agriculture (USDA), for example, provides consumers with nutrition information through sources such as the food guide pyramid and (jointly with the Department of Health and Human Services) the formulation of quantitative recommendations in the dietary guidelines for Americans. While such information campaigns have yielded positive results, a considerable gap remains between actual and healthful diets. Only 11% of men and 17% of women, for example, have diets that meet the recommendations for fat, saturated fat, and cholesterol (Tippett and Goldman).

Further dietary improvements may require nutritional education strategies to target specific population subgroups. Details on the usage of nutrition information at the individual consumer level may be helpful in this regard. Several recent empirical studies have addressed this objective by examining the role of nutrition information in food and nutrient intake (Carlson and Gould; Gould and Lin; Guthrie and Fulton; Ippolito and Mathios; Jensen, Kesavan, and Johnson; Kushi et al.; Putler and Frazao;

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Wang and Jensen). However, some of these studies have not used explicit measures of information, but instead have used variables such as education and income as proxies to capture information effects (Ippolito and Mathios; Kushi et al.). Others, while including direct measures of information, have treated such measures as exogenous determinants of intake (Guthrie and Fulton; Jensen, Kesavan, and Johnson; Putler and Frazao; Wang and Jensen). A limitation of these approaches is that key intake determinants such as income and education influence both intake and information simultaneously. Therefore, such determinants have both a direct and an indirect effect on intake—that is, the effect after holding information and other intake determinants constant as well as the effect acting through information. These effects cannot be separated without explicitly including information measures and treating them as endogenous determinants of intake.

The purpose of this study is to estimate the effect of nutrition information on cholesterol intake using direct information measures and treating those measures as endogenously determined. Previously, Carlson and Gould, and Gould and Lin addressed information endogeneity using a switching regression framework to model the impact of nutrition information on dietary fat intake. Kenkel used two-stage least squares to estimate the impact of information on smoking, alcohol use, and exercise. However, these studies did not focus on isolating the informational role of intake determinants. The special focus of this analysis is to separate the direct and indirect informational effects of an exhaustive set of personal and household characteristics that impact both information and intake. We seek to answer the following questions: To what degree does cholesterol information vary across different segments of the population? After controlling for the effects of other principal intake determinants, does increased information help individuals reduce their intake of cholesterol? and How does the effect of cholesterol information on cholesterol intake vary across the population?

We provide answers to these questions which are useful for targeting nutrition education programs, for food marketing and promotion, and for forecasting food consumption trends. In addition to investigating cholesterol intake, which has previously been examined only in the context of egg consumption, we use a more efficient specification than that used in our earlier study of dietary fiber (Variyam, Blaylock, and Smallwood 1996). The fiber study imposed the restrictive assumption that education, gender, and food program participation influenced intake solely through their effects on information. In this study, we use better identifying information to relax this assumption and show the direct and indirect effects of these variables.

Conceptual Framework and Data

Most of the economic analyses of health inputs and outcomes are based on Becker's 1965 theory of household production and on the 1971 characteristics model of consumer demand developed by Lancaster (e.g., Behrman and Deolalikar; Pitt and Rosenzweig; Senauer and Garcia). In this framework, households combine various inputs to produce "commodities," including the health of family members, to maximize a joint utility function. Some of the inputs (e.g., food, medical care) derive their value by supplying characteristics (nutrients, medical services) necessary for producing some commodities (health). Subject to the constraints of health production technology, time, and income, household utility maximization generates individual and household demand functions for the inputs and characteristics (Behrman and Deolalikar).

The reduced-form nutrient demand functions resulting from the above maximization framework have the general form:

$$(1) \qquad n = f(\mathbf{p}, I \mid \mathbf{x}, u),$$

where n is the amount of nutrient consumed, $\mathbf{p}$ is a vector of prices, I is the household income, $\mathbf{x}$ is a vector of individual and household characteristics, and u represents the unobserved individual effect.

Introducing nutrition information explicitly into the model reflects its role as a factor mediating part of the influence of $\mathbf{x}$ on nutrient intake, and thus the individual's health. For example, consider a key component of $\mathbf{x}$ education. Better educated persons are more efficient producers of health because they are better informed about the true effects of inputs on health; they have higher allocative efficiency, i.e., the ability to select a better input mix (Grossman and Kaestner). Education, therefore, affects health through information. Other personal characteristics that influence an individual's acquisition and use of information (e.g., income) also play a similar role in producing health.[1]

Making the role of information explicit, the reduced-form nutrient demand function and information equations may be written as:

$$(2) \qquad n = f(\mathbf{p}, I \mid \mathbf{x}, \mathbf{INFO}, u), \quad \text{and} \quad \mathbf{INFO} = g(\mathbf{z}, v),$$

where **INFO** is a vector of nutrition information variables; $\mathbf{z}$ is a vector of individual and household variables, some of which (such as education and income) may be common with $\mathbf{x}$; and v is an unobserved individual effect that may be correlated with u.

Information Measures and Explanatory Variables

The reduced-form intake and information equations (2) for cholesterol were estimated using data from the USDA's 1989–91 Continuing Survey of Food Intakes of Individuals (CSFII) and the companion Diet and Health Knowledge Survey (DHKS) (Cypel et al.). The CSFII gathered dietary intake data for members of a representative sample of U.S. households over a period of up to three consecutive days. The DHKS was a detailed 30-minute follow-up survey to the CSFII and was designed so that information from it could be linked to information on food intakes from the CSFII. Individuals identified in the CSFII as the main meal planner/preparer for the household were contacted approximately six weeks after they responded to the CSFII and asked a series of questions about their diet-health knowledge and attitudes. Because the DHKS was administered only to the main meal planner/preparer and not to the other members of the sample households, our analysis is restricted to the main meal planner/preparer.

[1] Personal characteristics also affect health production through productive efficiency—that is, through the amount of health output from given amounts of inputs and through tastes related to ethnic and cultural factors (Grossman and Kaestner).

After eliminating cases with missing values, our final sample consists of 3,800 observations out of 4,346 with complete three-day intake data.

Table 1 provides a listing of the variables used in the analysis. Cholesterol intake was measured by summing the level of cholesterol in each of the foods a respondent reported consuming over three consecutive days. On average, respondents in our final sample consumed 238 milligrams (mg) of cholesterol per day. Although this is less than the recommended level of 300 mg, the standard deviation is rather high at 137 mg. It should be noted that the CSFII-DHKS respondents were predominantly female; given their lower caloric intake than males, they were more likely to meet the cholesterol recommendation. Specifically, among the female respondents in the sample, 79% met the cholesterol recommendation, while the corresponding figure for male respondents was only 53%.

We use two DHKS questions to capture meal planners' cholesterol information level. The first measure ($INFO_1$) assesses the self-rated importance of avoiding too much cholesterol in one's own diet. Because the original 1–6 response scale to this question showed considerable skewness, we converted it to a 0–1 scale (where 1 = very important). The second measure ($INFO_2$) captures meal planners' awareness of health problems linked to cholesterol (1 = aware). This measure is similar to Kenkel's health knowledge measure in his study on smoking, alcohol use, and exercise.

Table 1 also identifies the independent variables hypothesized to affect information and/or intake. These variables fall into three broad categories: household characteristics, personal characteristics, and survey-related controls. Most of the household and sociodemographic variables, such as income, household size, age, sex, race, and schooling, have been used in previous nutrient intake studies (e.g., Behrman and Deolalikar; Gould and Lin; Morgan). The regional, urbanization, and survey-year dummy variables are expected to capture any cross-sectional price variation across households.

Income is represented by gross household income before taxes. Higher income may give better access to nutrition information, and thus indirectly affect cholesterol intake negatively (Ippolito and Mathios). Conversely, intake of meat products may rise as income increases, causing a positive direct effect. Which of these effects will dominate is uncertain, and must be determined empirically.

Schooling is predicted to have a negative indirect effect on cholesterol intake by increasing the allocative efficiency (Grossman and Kaestner; Ippolito and Mathios; Kenkel). However, as in the case of income, the direct effect of *Schooling* on intake due to variations in tastes is difficult to predict and is to be determined empirically.

The traditional role that females have played in food preparation/shopping leads us to expect they have higher stocks of nutrition information than males. The variables of race (*Black*), ethnicity (*Hispanic*), and *Age* are expected to capture variations in information and food preferences induced by cultural backgrounds and dietary habits. Both the household size (*Household Size*) and the presence of children in the household (*Children*) may increase the perceived benefits of gathering nutrition information and thus influence the meal planner's information level positively. These household variables may also influence intrahousehold allocation of resources and thus affect intake amounts, although the direction of their effects is unclear. Main meal planners who are employed only part time (*Part Employed*) or who are not employed (*Not Employed*) likely have more time available for food preparation, and hence nutrient

Table 1. Description of Variables

Variable Description	Name	Mean
DEPENDENT VARIABLES:		
▸ Cholesterol intake (milligrams)	—	238.2
▸ Importance of avoiding too much cholesterol in diet (1 = very important)	$INFO_1$	49.3
▸ Heard about health problems related to cholesterol (1 = yes, and identified circulation/heart problems)	$INFO_2$	72.4
INDEPENDENT VARIABLES:		
Household Characteristics:		
▸ Annual income before taxes ($000s)	*Income*	23.0
▸ Household size	*Household Size*	2.6
▸ Children present (< 20 years old)	*Children*	40.3
▸ Participated in WIC or FSP [a]	*Program*	16.6
▸ Region		
Midwest	*Midwest*	24.3
South	*South*	37.7
West	*West*	19.7
Northeast (omitted)	—	18.3
▸ Urbanization		
Suburb	*Suburban*	42.2
Nonmetro	*Nonmetro*	27.0
City (omitted)	—	30.8
Personal Characteristics:		
▸ Schooling (years)	*Schooling*	11.8
▸ Age (years)	*Age*	48.2
▸ Sex-Female	*Female*	83.1
▸ Race-Black	*Black*	13.9
▸ Ethnic origin-Hispanic	*Hispanic*	7.1
▸ Employment		
Not employed	*Not Employed*	55.2
Employed part time	*Part Employed*	13.8
Employed full time (omitted)	—	31.0
▸ Smoke cigarettes now	*Smoker*	25.7
▸ Vegetarian	*Vegetarian*	2.8
▸ On a special diet	*Special Diet*	17.5
▸ On a special low-fat diet	*Low-Fat Diet*	8.4
▸ On a special low-calorie diet	*Low-Calorie Diet*	5.2
▸ Disease[b]	*Disease*	22.2
▸ Body mass index	*BMI*	25.8
▸ Watch more than 5 hours TV/day	*TV5*	20.9
▸ Nutrition very important when shopping	*Nutri-Import*	61.0
▸ Compare nutrients when shopping		
Always	*Nutri-Comp1*	13.6
Sometimes	*Nutri-Comp2*	42.1
Rarely/Never (omitted)	—	44.3

Table 1. Continued

Variable Description	Name	Mean
Survey-Related Controls:		
▸ Year of CSFII-DHKS		
1991	*1991*	34.1
1990	*1990*	32.0
1989 (omitted)	—	33.9
▸ Amount of food eaten		
Day 1		
Less than usual	*LTU*1	17.7
More than usual	*MTU*1	6.4
Usual (omitted)	—	75.9
Day 2		
Less than usual	*LTU*2	13.2
More than usual	*MTU*2	3.4
Usual (omitted)	—	83.4
Day 3		
Less than usual	*LTU*3	12.4
More than usual	*MTU*3	3.6
Usual (omitted)	—	84.0

Notes: *Income, Household Size, Schooling, Age,* and *BMI* are continuous variables. The standard deviations are 22.3, 1.6, 3.1, 18.4, and 5.5, respectively. All other independent variables are dummy variables.
[a] WIC is Women, Infants, and Children Program; FSP is Food Stamp Program.
[b] Indicates a "yes" response to the question, "Has a doctor ever told you that you have heart disease/cancer/high blood cholesterol/stroke?"

intake may be affected (Horton and Campbell). The *Program* variable, defined as whether any member of the household participates in the Food Stamp Program (FSP) or the Women, Infants, and Children (WIC) Program, is included to capture the nutritional effects of program participation (Basiotis et al.).

Since grains, fruits, and vegetables are cholesterol-free foods, we expect vegetarians to have relatively lower cholesterol intakes. Smokers are probably less concerned about health issues and hence may possess less nutrition information than nonsmokers (McPhillips, Eaton, and Gans). The dummy variables *Special Diet*, *Low-Fat Diet*, and *Low-Calorie Diet* are included to control for the likely lower cholesterol intakes due to these dieting habits (Carlson and Gould). The body mass index (*BMI*), a ratio of the body weight (in kilograms) divided by the square of height (in meters), is included to control for the effects of variations in the amount of food consumed due to weight and height. We expect *BMI* to be positively related to cholesterol intake because foods rich in cholesterol are more energy dense than complex carbohydrates. Thus, individuals with higher *BMI*s may receive more of their calories from foods rich in cholesterol and fewer calories from foods rich in complex carbohydrates (Dattilo).

A meal planner's use of nutrition information sources is captured by whether the person watches five or more hours of television (*TV5*) each day, whether nutrition is very important while shopping for food (*Nutri-Import*), and whether the person compares nutrients while shopping (*Nutri-Comp*1, *Nutri-Comp*2). While some amount of television watching may help a person gain information, an excessive amount of five or more hours per day is likely to hinder rather than help information gathering by curtailing alternative activities such as reading (Carlson and Gould). Both the importance attached to nutrition while shopping and the habit of comparing nutrients while shopping are expected to be positively correlated with a respondent's nutrition information level (Gould and Lin; Moorman and Matulich). Finally, some variation in the intake data is likely to depend on whether the person reported each day's food intake to be less than usual or more than usual. Dummy variables with reported intake "usual" as the omitted category are used to control for these survey-related effects.

Empirical Model and Estimation Method

Our empirical version of (2) is specified as:

$$n = \alpha'\mathbf{x} + \beta_1 INFO_1 + \beta_2 INFO_2 + u, \tag{3}$$

and

$$INFO_j = \gamma_j'\mathbf{z}_j + v_j, \quad j = 1, 2, \tag{4}$$

where $INFO_j$ denotes the cholesterol information variables, $\mathbf{x}$ and $\mathbf{z}_j$ are vectors of exogenous variables, α and γ_j are conformable vectors of unknown coefficients, β_j are unknown scalar coefficients, and u and v_j are error terms distributed independently and identically across individuals but assumed to be correlated across the equations for the same individual. As noted earlier, $\mathbf{x}$ and $\mathbf{z}_j$ may have common variables such as education and income; it is these variables that have both a direct and an indirect effect on intake. Additionally, $\mathbf{z}_j$ must contain two or more variables that are not in $\mathbf{x}$ for identification.

As evident from table 1, the $INFO_j$ variables are observed on a binary scale. Let Y_j denote the observed binary responses of $INFO_j$ ($j = 1, 2$). Then, specifying a probit model,

$$Y_j = \begin{cases} 1 \text{ if } INFO_j > 0 \\ 0 \text{ otherwise,} \end{cases} \quad j = 1, 2, \tag{5}$$

and

$$\text{Prob}[Y_j = 1 \mid \mathbf{z}_j] = \Phi(\gamma_j'\mathbf{z}_j), \quad j = 1, 2, \tag{6}$$

where Φ represents the normal CDF.

Given the correlation between the error terms of equations (3) and (4), ordinary least squares (OLS) estimation of (3) is inconsistent due to simultaneous equations bias. We use a generalized probit minimum distance estimator (MDE) to obtain consistent estimates of the unknown parameters of equations (3)–(4). The minimum distance method estimates the unknown structural parameters by iteratively minimizing a quadratic distance function between estimates of the reduced-form equations and the structural parameters underlying the reduced form. This estimator is consistent and asymptotically more efficient than Heckman's two-step procedure (Chamberlain; Newey).

Empirical Results

Table 2 reports estimates of the information equations (4) and the intake equation (3).[2] The intake effects of excessive television watching (*TV5*), comparison of nutrients while shopping (*Nutri-Comp*1, *Nutri-Comp*2), and importance of nutrition while shopping (*Nutri-Import*) are assumed to be due purely to informational differences. Therefore, these variables enter the information equations only. The *BMI* and the dummy variables indicating less than usual and more than usual intakes are assumed to have no informational effects, and hence these variables enter the intake equation only. The R^2s for the binary information variables are pseudo-R^2s proposed by Laitila. The R^2 for the intake equation was computed using the traditional formula after substituting (4) into (3). The R_M^2 is a McFadden-type goodness-of-fit measure for the entire model, computed as $R_M^2 = (Q_b - Q_M)/Q_b$, where Q_b and Q_M are the minimized values of the minimum distance function for a base model and the hypothesized model, respectively. The base model is a restricted model in which the intake and information equations are constrained to include only the intercepts. The R_M^2 is 0.818, indicating a good fit relative to a model that includes only the intercept. The R^2s for the information and intake equations are in the range typical for cross-section data.

Turning to the effects of nutrition information variables, the estimate of the $INFO_1$ coefficient is negative and significant at the 1% level. Greater self-assessed importance of avoiding too much cholesterol therefore translates into lower cholesterol intake. The $INFO_2$ coefficient estimate is negative and significant at the 10% level. Thus, better awareness of cholesterol-related health problems leads to a significant reduction in cholesterol intake. These results confirm that, holding a variety of consumer characteristics constant, greater nutrition information translates into lower cholesterol intake.

The $INFO_2$ coefficient estimate is more than three times the $INFO_1$ coefficient estimate in size. This size differential has an economic interpretation given the distinction in the aspects of nutrition information these variables are measuring. $INFO_2$ measures consumers' ability to name a specific health problem due to excess cholesterol intake, whereas $INFO_1$ probes their general notions about cholesterol control, unrelated to any specific diet-health link. Since the economic cost of excess cholesterol intake for the individual stems from the resulting health problems, $INFO_2$ is a better measure of the individual's awareness of this cost, and thus has a larger effect on intake than $INFO_1$.

The cholesterol intake was expressed in logarithm form since it gave a better fit. *Income* and *BMI* also were converted to logs to capture possible nonlinearities. Thus, coefficients of *Income* and *BMI* are elasticities. The coefficients of *Age*, *Schooling*, and

[2] Models with a variable measuring meal planners' knowledge of the cholesterol content of foods also were estimated. This variable did not account for any variation in cholesterol intake beyond that explained by $INFO_1$ and $INFO_2$. Therefore, these results are not reported here. (The full set of results is available in Variyam, Blaylock, and Smallwood 1997.)

Table 2. Cholesterol Information and Intake Equation Estimates

Independent Variable	$INFO_1$	$INFO_2$	Intake
$INFO_1$	—	—	-0.066**
			(2.44)
$INFO_2$	—	—	-0.243*
			(1.86)
Log *Income*	0.008	0.159***	0.089***
	(0.24)	(4.86)	(3.28)
Schooling (years × 10^{-1})	0.015	0.627***	0.121
	(0.18)	(7.42)	(1.28)
Age (years × 10^{-1})	0.029*	-0.039**	-0.038***
	(1.79)	(2.37)	(3.94)
Female	0.136**	0.071	-0.364***
	(2.31)	(1.21)	(11.35)
Black	-0.061	-0.381***	0.027
	(0.92)	(5.74)	(0.46)
Hispanic	-0.225**	-0.499***	-0.094
	(2.52)	(5.93)	(1.18)
Part Employed	-0.020	0.150**	-0.051
	(0.29)	(2.05)	(1.27)
Not Employed	-0.075	0.076	0.010
	(1.31)	(1.30)	(0.33)
Children	0.040	-0.028	0.058
	(0.58)	(0.39)	(1.57)
Household Size	-0.019	0.003	-0.013
	(0.91)	(0.15)	(1.16)
Log *BMI*	—	—	0.215***
			(4.92)
Smoker	-0.049	0.071	0.012
	(1.00)	(1.41)	(0.47)
Vegetarian	0.131	-0.132	-0.365***
	(1.01)	(0.93)	(6.88)
Special Diet	0.193**	0.047	0.029
	(2.33)	(0.55)	(0.70)
Low-Fat Diet	0.207**	0.156	-0.025
	(1.99)	(1.50)	(0.44)
Low-Calorie Diet	-0.069	0.035	-0.155***
	(0.62)	(0.31)	(2.71)
Disease	0.267***	0.077	-0.008
	(4.74)	(1.34)	(0.27)
Program	0.023	-0.065	0.066*
	(0.34)	(0.96)	(1.88)
Midwest	-0.086	0.076	-0.020
	(1.31)	(1.11)	(0.56)
South	0.121**	0.002	-0.034
	(1.99)	(0.04)	(1.08)
West	0.012	-0.052	-0.008
	(0.17)	(0.72)	(0.23)

Table 2. Continued

Independent Variable	$INFO_1$	$INFO_2$	Intake
Suburban	-0.123**	0.001	-0.031
	(2.38)	(0.01)	(1.12)
Nonmetro	-0.159***	-0.118**	0.007
	(2.79)	(2.05)	(0.23)
1990	0.010	-0.247***	-0.076*
	(0.19)	(4.74)	(1.84)
1991	-0.018	0.058*	-0.040
	(0.34)	(1.88)	(1.49)
TV5	0.029	-0.146***	—
	(0.55)	(2.87)	
Nutri-Import	0.699***	-0.092**	—
	(15.44)	(2.03)	
*Nutri-Comp*1	0.431***	0.128**	—
	(6.33)	(2.01)	
*Nutri-Comp*2	0.235***	0.097**	—
	(5.15)	(2.23)	
*LTU*1	—	—	-0.078***
			(3.25)
*MTU*1	—	—	0.107***
			(2.95)
*LTU*2	—	—	-0.176***
			(6.51)
*MTU*2	—	—	0.091*
			(1.73)
*LTU*3	—	—	-0.127***
			(4.75)
*MTU*3	—	—	0.080
			(1.59)
Intercept	-0.873***	-1.603***	4.327***
	(2.67)	(4.76)	(13.92)
Scale Factor[a]	0.399	0.361	—
R^2	0.203	0.170	0.151
R_M^2	—	—	0.818

Notes: Single, double, and triple asterisks (*) denote significance at the 10%, 5%, and 1% levels, respectively. Numbers in parentheses are absolute t-values.
[a] The scale factor, $\phi(\hat{\gamma}'\bar{\mathbf{z}})$, multiplied by a coefficient estimate gives the predicted change in probability of the information variables due to a change in the corresponding explanatory variable.

Household Size give the percentage change in cholesterol intake in response to a unit change in each variable. The remaining independent variables are dummy variables; their coefficients can be interpreted as the approximate percentage change in intake for the respective category compared with the base category (the exact percentage change is given by 100[exp(α) - 1], where α is the coefficient). All estimates related to the intake equation are for cholesterol intake per day.

Table 3. Average Predicted Change in Cholesterol Intake Due to Change in Selected Independent Variables (in milligrams)

Independent Variable	Direct Effect	Indirect Effect		Total Effect
		$INFO_1$	$INFO_2$	
Income [a]	18.33***	-0.11	-7.96*	10.27***
Schooling [b]	2.50	-0.02	-3.14*	-0.67
Age [b]	-0.78***	-0.04	0.20	-0.62***
Female	-84.86***	-2.09*	-4.05	-91.00***
Black	5.90	0.87	19.96*	26.73***
Hispanic	-19.68	3.11*	25.46*	8.89
Part Employed	-10.20	0.27	-7.28	-17.22***
BMI [a]	44.32***	—	—	44.32***
Smoker	2.56	0.67	-3.58	-0.39
Vegetarian	-64.30***	-1.52	5.65	-60.18***
Special Diet	5.98	-2.65*	-2.38	0.94
Low-Fat Diet	-4.58	-2.58	-7.20	-14.36*
Low-Calorie Diet	-29.13***	0.86	-1.62	-29.89***
Disease	-1.72	-3.58**	-3.81	-9.11*
Program	14.07*	-0.32	3.35	17.09***
TV5	—	-0.40	7.37*	6.97*
Nutri-Import	—	-9.51***	4.62	-4.89
Nutri-Comp1	—	-5.72**	-6.27	-11.99***
Nutri-Comp2	—	-3.18**	-4.86*	-8.04***

Note: Single, double, and triple asterisks (*) denote that corresponding coefficient estimates are significant at the 10%, 5%, and 1% levels, respectively.

[a] Figures represent a doubling of *Income* and *BMI*, respectively.

[b] Figures represent an additional year of *Schooling* and *Age*, respectively.

The coefficients of the explanatory variables appearing in the intake equations give the direct effects of these variables on intake. Additionally, the explanatory variables in the information equations have indirect effects on intake. These indirect effects can be estimated by substituting the estimated information equations into the intake equation. The sum of direct and indirect effects gives the total effect of an explanatory variable on intake. For each explanatory variable, the direct, indirect, and total effects can be translated into predicted changes in intake due to a change in that explanatory variable, holding other explanatory variables constant. Table 3 reports the predicted direct, indirect, and total effects of selected explanatory variables.

Income has a significant positive direct effect on cholesterol intake. This implies that, conditional on a constant level of nutrition information and other characteristics, those with higher income tend to consume diets richer in cholesterol than those with lesser income. This result is similar to the positive, direct effect for income on fat and saturated fat intake found by previous researchers (Carlson and Gould; Gould and Lin; Variyam, Blaylock, and Smallwood 1997), and is likely due to the increased preference at higher income levels for meats and less nutritious processed foods.

The predicted direct effect for a doubling of income is an increase of 18 mg in cholesterol intake. At the same time, however, those with higher income tend to have substantially greater diet-health awareness, as indicated by the positive and highly significant income coefficient for $INFO_2$ in table 2. Based on the estimated scale factor [computed as $\phi(\hat{\gamma}'\bar{\mathbf{z}})$], an additional $10,000 in annual household income results in a 2.5% increase in the probability of being aware of specific health problems due to too much cholesterol intake. As shown in table 3, a higher awareness level due to higher income is predicted to lower cholesterol intake by 8 mg. Thus, the informational effect of income reduces the direct income effect by 44% so that the total income effect is only 10 mg.

Although the predicted direct effect of *Schooling* is 2.5 milligrams, the *Schooling* coefficient itself is insignificant (table 3). As expected, *Schooling* has a significant positive effect on diet-health awareness (table 2). An additional year of schooling increases the probability of being aware of the link between cholesterol intake and health problems by 2%. This indirect informational effect of schooling reduces cholesterol intake by 3 mg. However, the indirect effect is not strong enough to render the negative total effect significant. Economists have suggested that a major non-monetary benefit of education is better health from better health behavior. As noted earlier, a hypothesis linking these effects is that schooling promotes better health behavior through greater acquisition and more efficient use of health information (Grossman and Kaestner). Our schooling results support this hypothesis by showing that the beneficial effect of education is purely information related.

All else constant, cholesterol intake decreases with age. An additional year of age decreases cholesterol intake by about four-fifths of a milligram. Interestingly, age has opposite effects on the two information variables. While the self-rated importance of reducing cholesterol ($INFO_1$) increases with age, diet-health awareness ($INFO_2$) actually decreases. These indirect effects, however, are not strong enough to substantially change the negative direct effect from age-related tastes and preferences; thus the total effect of age is negative and significant (table 3).

Body mass, as expected, has a positive effect on cholesterol intake. This finding is in accord with Wang and Jensen's finding of a positive effect for *BMI* on egg consumption. A doubling of *BMI* increases cholesterol intake by 44 milligrams (table 3). Since *BMI* may be endogenous, we estimated the model after excluding *BMI*, as well as some other variables that may have some degree of endogeneity. The coefficients of variables common to both specifications, particularly the information effects, did not change in sign or significance. (These additional results are available in Variyam, Blaylock, and Smallwood 1997.)

Since women consume less food than men, the direct gender effect is expected to be substantial. This is confirmed in table 3. Female cholesterol intake, ceteris paribus, is 85 mg lower than that for males. Also as expected, women tend to attach greater importance to the avoidance of too much cholesterol in the diet than men. This indirect informational effect reduces their cholesterol intake by an additional 2 mg over their male counterparts.

While the information effect is small compared with the direct effect for females, the information effects are substantial for Blacks and Hispanics. Controlling for other characteristics, both groups have lower diet-health awareness levels compared with Whites and non-Hispanics, respectively. For Blacks, this lower awareness level reinforces the positive but insignificant direct effect so that the predicted total effect is to increase Black cholesterol intake by 27 mg compared with Whites. For Hispanics, the direct effect that lowers their cholesterol intake by 20 mg compared with other ethnic groups is offset by the indirect informational effect that increases their cholesterol intake. The total effect is a 9 mg higher cholesterol intake by Hispanics, which, although sizable, is statistically insignificant. The clear implication of these results is that Blacks and Hispanics stand to benefit considerably from better information about diet-health relationships.

Vegetarians, due to their intake of low-cholesterol foods, are predicted to have substantially lower cholesterol intake than nonvegetarians. As expected, the direct effect, rather than the indirect effects, is predominant—indicating that a vegetarian diet in itself is contributing to lower intake rather than higher information levels of vegetarians.

Dieting status has a significant influence on cholesterol intake with two notable results. First, those on a low-calorie diet achieve much lower cholesterol intake than those on a low-fat diet. Second, the low-fat diet effect is principally indirect, while the low-calorie diet effect is principally direct. This and similar results for fat and saturated fat (Variyam, Blaylock, and Smallwood 1997) may indicate that a substantial part of the national trend toward lower intakes of fats and cholesterol has been achieved through diet changes related to weight control. Putler and Frazao argue that individuals attempting to reduce fat intake often substitute one source of fat for another (such as substituting meat with fat-rich dairy products), thus limiting the impact on their net fat intake. A low-calorie diet may require watching both fat and carbohydrate intakes, so that there is less substitution of one fat source for another.

The results for the *Disease* variable are as expected. Those with a chronic health condition, such as a high blood cholesterol level, are significantly more likely to think it is important to limit cholesterol in their diet—possibly because they are under the care of a doctor or health specialist. This higher importance translates to approximately 3.5 mg lower cholesterol intake. While both the direct effect and indirect effect through diet-health awareness are negative, the corresponding coefficient estimates are insignificant. The total effect of having a chronic health condition is to reduce cholesterol intake by 9 mg on average, compared to those without a health condition. Wang and Jensen obtained a similar significant negative total effect for the *Disease* variable on egg consumption. However, since they did not account for the endogeneity of information, they could not separate the informational effect.

Controlling for other factors, household participation in the Food Stamp or WIC programs (*Program*) has a positive and significant direct effect on cholesterol intake. Most of the total effect is through dietary differences. One reason may be because WIC subsidizes consumption of eggs, and program participants get a larger share of cholesterol from eggs (30.4%) compared with nonparticipants (24%). The lack of information effects for program participation suggests that existing nutrition education strategies embodied in these programs may not be having the desired effect. Among other household characteristics, region, presence of children, and household size have no systematic direct or informational effects on cholesterol intake. However, residence in a nonmetro area is significantly related to lower $INFO_1$ and $INFO_2$ levels compared with residence in a city. This suggests a possible need to target nutrition information campaigns toward nonmetro residents.

Excess television watchers (*TV5*) have a lower diet-health awareness, likely because they have less time for information-enhancing activities such as reading. Ceteris paribus, this is predicted to increase their cholesterol intake by 7 mg. Comparing nutrients on food labels always (*Nutri-Comp*1) or sometimes (*Nutri-Comp*2), as opposed to never, translates to 12 and 8 mg reductions in cholesterol intake, respectively. These results are similar to the findings of Carlson and Gould, and Gould and Lin. Accounting for these effects, the *Nutri-Import* variable, indicating self-rated importance of nutrition while shopping, does not have much added explanatory power.

Although the results suggest a lower intake of cholesterol by part-time employees (*Part Employed*), the model could not precisely separate the direct and informational effects. The insignificant effect for those not employed outside the home is surprising given that the expected effect is through greater time available for food preparation (Horton and Campbell). The lack of significance of the *Smoker* coefficient is also somewhat surprising given the findings of McPhillips, Eaton, and Gans, and of Variyam, Blaylock, and Smallwood (1996) which suggest that smokers tend to have less healthful diets than nonsmokers.

Conclusion

Our results confirm that nutrition information affects intake of cholesterol. This evidence adds to previous findings for fat and saturated fat (Carlson and Gould; Gould and Lin; Variyam, Blaylock, and Smallwood 1997); for dietary fiber (Variyam, Blaylock, and Smallwood 1996); and for eggs (Wang and Jensen). These cross-sectional results supplement time-series informational effects found by previous researchers (Brown and Schrader; Capps and Schmitz; Chern, Loehman, and Yen). Together, these findings show that consumers have absorbed and used the information linking diet and health in their gradual shift toward more healthful diets.

The findings also suggest a continued need for nutrition education to close the persistent gap between actual and healthful diets. In this regard, our study has quantified the informational effects of various consumer characteristics on dietary intakes. Our findings on the differing effects of income, schooling, age, gender, race, ethnicity, dieting status, and program participation through direct and indirect effects may be useful for guiding nutrition education programs. A similar analysis of food groups may be the next step for identifying specific dietary changes that can be promoted by targeted nutrition information efforts.

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